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CRUDE OIL PRICE VOLATILITY SPILLOVERS INTO OTHER ASSET CLASSES

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Introduction

Crude oil price volatility (oil price) has long been of concern among policy makers because of its potential effects on the global economy. The reliance on crude oil continues to grow, especially among the largest emerging economies. According to Martensen (2013), between 2005 and 2011, the growing economies of China and India increased their use of crude oil by 36% and 22% respectively. Martensen (2009) estimates that a percent growth in global GDP is associated with a twenty five basis-point rise in crude consumption. Rising prices have in the past been associated with cost-push inflationary pressures and falling prices with the expectations of economic slowdown. More recent price declines have been associated with supply pressures, arising, at least partly, from the rapid growth of shale oil production.

The extent to which the volatility of oil prices spills over to equity and other markets is of obvious importance to traders. Questions on spillovers to commodities are of particular importance to nations heavily dependent on commodity exports or imports. Petroleum products play a direct and important role in the production of most agricultural commodities. But the relationship between price of crude oil and other commodities may also have a speculative/investment origin. For instance, Adrangi et al. (2015) discuss the inflationary and recessionary effects stemming from crude oil price volatility, and the resulting portfolio adjustment efforts by investors. This portfolio adjustment may impart an upward trend in precious metal prices and commodity prices, which may exacerbate inflationary pressures.

The price of crude oil also remains relevant to the developed world. In recent years, the US has joined the league of major crude oil producers, ranking the third crude oil producer, only behind Russia and Saudi Arabia (e.g., Bell (2014)). These trends undoubtedly help the US current account balance. Nevertheless, the US market remains subject to forces of the world crude oil market and its unpredictability due to many geopolitical variables out of its control. Despite the

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relative independence of the US energy markets, the economies of US trading partners are heavily dependent on crude oil resources of the world. This link continues to leave the US vulnerable to the global crude oil market uncertainties.

Rising oil prices have always been associated with cost push inflation as firms in economies of the world absorb higher energy costs. Rising costs normally lead to falling corporate profits, as global competition keeps output prices somewhat in check. Higher inflationary pressures lead to higher interest rates, thus, falling equity prices, which are the present value of future cash flows. In a similar manner, inflation may be tied to the value of the dollar and other asset classes. As inflationary pressures build up, the US Federal Reserve Bank (the Fed), which targets the inflation rate, may be forced to raise short term interest rates. Rising interest rates are likely to help the exchange rate of the dollar in the short-run, but may result in dampening economic growth in the longer run. Thus, interest rate changes will have an unpredictable effect on the dollar, and by extension, commodities priced in it.

This paper examines the volatility spillovers among crude oil, equity markets and commodity markets in the post Great Recession era, one in which crude oil prices witnessed extreme price variability. Our research is motivated by several issues. First, geopolitical, environmental, accessibility and the economics of extraction will likely continue to weigh on volatility in oil prices in the coming decades. As Adrangi et al. (2015) detail, due to technological innovations and the production-substitutability of energy sources, crude oil price volatility continues to spread to other energy sources, and vice versa. Second, the volatility in markets for commodities, equities, precious metal markets and currencies are matters of concern for the public, traders, and policy makers. For many economies of the world, commodity price behavior is central to their economic performance. Finally, much of the earlier research in the transmissions from crude oil to other assets have failed to consider the nonlinear dependencies in the price data fully.

Prior research has examined causality, cointegration, the short-run and long-run relationships between crude oil price shocks, macroeconomic variables and equities markets. Notable among them are Leblanc and Chinn, (2004), Jones et al. (2004), Labonte (2004), Klein et al. (2005), and Greenspan (2005). Other researchers discuss the possibility of nonlinear transmission channels as well chaotic structures in various financial markets. Articles by Blume, Easley, and O'Hara (1994), Bohan (1981), Brock, Lakonishok, and LeBaron (1992), Brush (1986), Clyde and Osler (1997), Pruitt and White (1988, 1989), and Taylor (1994), fall in this category. Researchers note that econometric models that are suitable in the absence of nonlinear behavior may not be appropriate in the presence of nonlinear dependence in the data. Studies that are based on vector autoregressive-, cointegration- and vector error correction models, and Granger causality tests in a linear framework, may produce spurious findings. Time series that are nonlinear in mean are characterized by higher order moments such as variance, skewness, and kurtosis that are nonzero. In these instances, Autoregressive Conditional

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Heteroscedasticity (ARCH) type models, and nonlinear Granger causality frameworks are likely to represent better tools (e.g., Adrangi et al. (2001(a), 2004).

In this article, we first test for nonlinear behavior via portmanteau tests of chaos, including the test suggested by Brock, Dechert, and Scheinkman (1987) [i.e. the BDS statistic, and correlation dimension]. To this end, we filter each series through Autoregresive (AR) and Generalized ARCH (GARCH) frameworks and test their innovations for remaining nonlinearities including chaotic behavior. These steps aid in the selection of the appropriate econometric approach.

The price data exhibit nonlinearities in all cases. However, as shown by Adrangi et al. (2015), GARCH (1,1) model and its variations are well-positioned to capture at least some of the nonlinearities in the first and second moments. Therefore, we estimate bivariate GARCH (1,1) and Asymmetric GARCH (1,1) models for crude oil price and other assets. Our findings support the notion that the direction of price information flow is from the crude oil market to others. Our nonlinear Granger causality tests present evidence that point to causality between oil prices and other assets. Our empirical results also offer confirmation for the important role of crude oil in the economy, including in agriculture. These results are consistent with governmental policy of managing strategic reserves for volatility dampening purposes.

The remainder of this article is organized in the following manner. In the second section we summarize the related research. The third section discusses the data and methodology. The fourth and fifth sections present the summary statistics and main empirical findings, respectively. The sixth and final section summarizes and concludes the article.

Related Research

While there is a substantial body of research on the association between the volatility of crude oil and equity market behavior, the same is not true for agricultural commodities, currencies, or precious metals. For instance, Sadorsky (2004), among many others, suggests risk premiums result from oil price volatility, which might explain the negative relationship between oil price volatility and equity prices. Could similar arguments be made for the association between oil price volatility and currency and commodity prices? Here, we briefly summarize research that is relevant to the current study. Much of this research is discussed in greater detail by others, for instance, Adrangi et al. (2015). The majority of articles examine the impact of crude oil price volatility on the behavior of equity markets. Relatively few papers investigate the crude oil price association with commodities (mostly precious metals) and currencies. We summarize this research and examine their methodologies.

Before 2000, several papers examine the relationship between crude oil (or energy) prices and equity markets of developed economies. Chen, Roll, and Ross (1986), Kaneko and Lee (1995), Ferson and Harvey (1994), Jones and Kaul (1996), Huang et al. (1996), Sadorsky (1999), Faff and Brailsford (1999), among others fall into this category. These studies employ autoregression, cointegration, and vector error corrections models (VECM). Sadorsky (1999) and Faff and Brailsford (1999), among others, find strong evidence that crude oil prices and equity prices are related, while Huang et al. (1996)), among others, others do not.

In the post 2000 period, a large number of articles examine the association between crude oil prices and equity prices of the developing world. Notable among them are Hondroyiannis and Papapetrou (2001), Hammoudeh and Aleisa (2002), Filis et al. (2011), Sadorsky (2003), Hammoudeh and Eleisa (2004), El-Sharif et al. (2005), Huang et al. (2005), Basher and Sadorsky (2006), Park and Ratti (2008), Miller and Ratti (2009), Chiou and Lee (2009), Narayan and Narayan (2010), Zhu et al. (2011), and Basher et al. (2012). Like the pre-2000 group of scholars, these researchers deployed tools such as auto-regression, threshold auto-regression, vector error correction, variations of the GARCH models, and Granger causality tests. They find that crude oil price volatility and equity market behavior are related.

Closer to the topic of this research, Soytas et al. (2009) employ Toda-Yamamoto causality tests to investigate the information transition from world oil prices to interest rates, the lira–US dollar exchange rate, and the spot prices for gold and silver in Turkey. They are unable to establish any informational role of global oil prices in predicting precious metal prices, interest rates, or the lira exchange rate. As expected, oil prices are not influenced by the domestic money market and precious metal markets in Turkey. However, some transitory and positive effects of oil price innovations on the Turkish gold and silver markets are found.

Sari et al. (2010) deploy autoregressive distributed lag models to investigate the co-movements and information transmission among the prices of precious metals and crude oil, and the US dollar/euro exchange rate. They find the long-run equilibrium relationships to be weak, but find evidence of strong short-run feedback. The precious metals markets respond significantly but temporarily to price shocks to the other metals and the exchange rate. Furthermore, they uncover some evidence of market overreactions in the palladium and platinum prices, as well as in the exchange rate.

The current study contributes to the literature by explicitly recognizing that nonlinearity in the data will provide more robust answers to the relationships. Our article tests for the presence of nonlinearities in each price series and deploys frameworks most consistent with the nature of the data. This approach of systematically establishing the underlying series structures before deploying models is superior to ad hoc methodologies and relies on an empirical foundation. Models that are linear in nature and designed for series that demonstrate linear underlying behavior would be inappropriate for detecting nonlinear relationships. A brief description of the methodology follows.

Methodology

Preliminary to our analysis of the volatility relationships among crude oil price and other assets, we test each of the price series for stationarity and non-linearity.

A significant part of the methodology used in this paper has been used by authors in various past research (e.g., Adrangi at al. (2001 (a,b), 2004, 2015)). Therefore, we only briefly describe these methodologies here.

To test for nonlinearities and the existence of chaotic behavior, we apply the Brock, Dechert, and Scheinkman (1987) test (BDS) and Correlation Dimension tests of chaos to each series. While we show nonlinearities in returns series, our tests indicate that these nonlinearities are not stemming from the chaotic structure. We estimate autoregressive and bivariate GARCH (1,1) models of return series. A brief description of these tests and frameworks follows.

Testing for Chaos

Deterministic chaos, or more simply—chaos, in the context of an economic or financial time series, refers to its complex behavior that is fully determined by (and thus is non-random in) its initial condition. Chaotic series are deemed impossible to predict since indiscernible differences in the initial conditions will yield very divergent outcomes. Therefore, a chaotic price series may be thought of as one in which complex nonlinear patterns exist, but may be apparent only after the fact. Chaotic series are deterministic, but whose divergence from norm grows exponentially. Not surprisingly, neither linear nor nonlinear statistical tests of association can be expected to yield meaningful results for chaotic series.

The common method for distinguishing deterministic processes from other processes is to recognize that the former evolves in the identical fashion from a point in time. Therefore, if one could search time series for behavioral similarities in neighboring states, and measure the difference (error) between the evolutions, a stochastic process will have a randomly distributed error, a deterministic process will have an error that remains stable, and a deterministic chaotic system will have an error that increases indefinitely. Extensive discussions of the common tests of chaos may be found in Adrangi et al. (2001a, 2001b, and 2004). Therefore, we only discuss these briefly them here. The two tests of chaotic behavior that are employed are (a) Correlation Dimension (Grassberger and Procaccia (1983) and Takens (1984)), and (b) the test suggested by Brock, Dechert, and Scheinkman (1987), i.e. the BDS statistic.

Correlation Dimension

Consider a stationary time series xt, t =1...T. If we embed xt in a m-dimensional space by choosing M-histories starting at each time, t: $x_t^2 = \{x_t, x_t+1\}$,.., $x_t^M = \{x_t, x_t+1, \ldots\ldots, x_t+M-1\}$, the M-histories may be used to recreate the dynamics of the underlying system (Takens (1984)). For some dimension M and a distance ε, the correlation integral is given by

$$C^M(\varepsilon) = \lim_{T\to\infty} \{\text{the number of (i,j)} \text{ for which } \left\|x_i^M - x_j^M\right\| \le \varepsilon\}/T^2, \quad (1)$$

Where $\| \|$ is the distance induced by the norm. For small values of ε, $C^M(\varepsilon) \sim \varepsilon^D$, where D is the dimension of the system (see Grassberger and Procaccia (1983)). The correlation dimension in embedding dimension M is

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$$D^M = \lim_{\varepsilon \to 0} \lim_{T \to 0} \{\ln C^M(\varepsilon)/\ln \varepsilon\}, \tag{2}$$

the correlation dimension is given by

$$D = \lim_{M \to 0} \ln D^M. \tag{3}$$

ollowing Brock and Sayer (1988), our estimate for correlation demention is given by the statistic,

$$SC^M = \frac{\{\ln C^M(\varepsilon_i) - \ln C^M(\varepsilon_{i-1})\}}{\{\ln(\varepsilon_i) - \ln(\varepsilon_{i-1})\}} \tag{4}$$

several dimensions M (Brock and Sayers (1988)). The SC^M statistic is a local estimate of the slope of the C^M versus ε function. Following Frank and Stengos (1989), we compute the average of the three largest values of SC^M for each embedding dimension.

BDS Statistics

Brock, Dechert, and Scheinkman (BDS, 1987) suggest a statistical test based on correlation integral that has been deployed as a portmanteau test in the detection of various types of nonlinearity and deterministic chaos. BDS demonstrate that when xt is (i.i.d) with nondegenerate distribution,

$$C^M(\varepsilon) \to C^1(\varepsilon)^M \quad , as \quad T \to \infty \tag{5}$$

fixed M and ε. The statistic

$$W^M(\varepsilon) = \sqrt{T}\,\{[C^M(\varepsilon) - C^1(\varepsilon)^M]/\sigma^M(\varepsilon)\}, \tag{6}$$

re σM, is the standard deviation of [·], has a limiting standard normal distribution under the null hypothesis of IID. W^M is known as the BDS statistic. Nonlinearity will be established if W^M is significant for a stationary series. If the nonlinear structure arises from a known non-deterministic system, then chaos may be ruled out.

Bivariate GARCH Models

Based on our findings on the time-series nature of returns, we estimate bivariate VAR-GARCH(1,1) models that include oil price percentage changes and other asset return series one at a time. The following VAR model will be estimated for the asset returns:

$$R_{it} = \alpha_i + \sum_{j=1}^{2} \alpha_{ij} R_{i,t-1} + u_{i,t} \qquad \text{i,j=1,2,} \tag{7}$$

where the variance is permitted to vary with time,

$$\sigma^2_{i,t} = \beta_i + \gamma_i u^2_{i,t-1} + \varphi_i \sigma^2_{t-1} \quad i=1,2. \tag{8}$$

The above framework is commonly employed to study the volatility behavior in financial markets (e.g., Kyle (1985), Shiller (1979) and Singleton (1980)), Weiss (1984), Engle, Ng, and Rothschild (1990), and Engle, Lilien, and Robins (1987)).

To investigate the volatility spillovers and information arrival in the context of our paper, we propose the VAR version of equation (8) that acconts for the variance and covariance persistence (e.g., Adrangi et al. (2015), Hamao, Masulis, and Ng (1990), Chan, Chan, and Karolyi (1991). The following bivariate GARCH equations are estimated:

$$\sigma^2_{1,t} = \alpha_0 + \alpha_1 \sigma^2_{1,t-1} + \alpha_2 \varepsilon^2_{1,t-1} + \alpha_3 \varepsilon^2_{2,t-1}, \tag{9}$$

$$\sigma^2_{2,t} = \beta_0 + \beta_1 \sigma^2_{2,t-1} + \beta_2 \varepsilon^2_{2,t-1} + \beta_3 \varepsilon^2_{1,t-1}, \tag{10}$$

$$\sigma_{12,t} = \gamma_0 + \gamma_1 \sigma_{12,t-1} + \gamma_2 \varepsilon_{1,t-1} \varepsilon_{2,t-1}, \tag{11}$$

Assuming

$$\begin{pmatrix} \hat{\varepsilon}_{1,t} \\ \hat{\varepsilon}_{2,t} \end{pmatrix} \Big| \Omega_{t-1} \_StudentT\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2_{1,t} & \sigma_{1,2,t} \\ \sigma_{1,2,t} & \sigma^2_{2,t} \end{pmatrix}, \Theta \right)$$

Where, $\sigma^2_{1,t}$ and $\sigma^2_{2,t}$ are the variances of $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$, conditional on information set (Ω) available at t-1, $\sigma_{1,2,t}$ represents the conditional covariance, ε_{it} are randomly distributed errors, and Θ is the degrees of freedom in the Student t distribution. The constant conditional correlation coefficient is provided by

$$\rho_{12} = \sigma_{1,2,t} (\sigma^2_{2,t} \sigma^2_{1,t})^{-\frac{1}{2}}.$$

The correlation between oil price and other asset markets may be dynamic on the underlying volatilities of these assets. To accommodate this possibility, we estimate, and present results of the dynamic conditional correlation (DCC) derived from the GARCH estimates as follows:

$$\rho_{ij}(t) = M_{ij}(t) / \sqrt{M_{ii}(t) M_{jj}(t)},$$

re M represents modified diagonal covariance matrix from the GARCH model.

The parameters α_2 and $ß_2$ in (9) and (10) are the measures of the persistence of volatility. The large values of these parameters indicate that the high conditional variance persists for a stretch of time following shocks to asset prices. Parameters α_3 and $ß_3$ capture the volatility spillovers between markets. For instance, $\alpha_3>0$ and $ß_3=0$ will be consistent with the hypothesis that the volatility spills over from the second asset to the first, but not *vice versa*.

The log likelihood function is given by

$$\mathrm{L}(\Omega) = -.05 * \mathrm{Ln}\ |\Lambda_t| - 0.5\ \ \varepsilon_t^{'} \Lambda_t^{-1} \varepsilon_t,$$

re Ω is a vector model parameters, $\varepsilon'_t = [\varepsilon_{1,t}, \varepsilon_{2,t}]$ is the vector of innovations, Λ_t is the 2x2 time-varying variance covariance matrix with diagonal elements given by equations (9) and (10), and the off-diagonal covariances given by equation (11).

Finally, we also deploy the Exponential GARCH (EGARCH) model to account for asymmetric shock response within and across markets. The bivariate EGARCH model is an extension of the univariate EGARCH model of Nelson (1991). The estimated bivariate EGARCH model parameters may be tested and used to measure the asymmetric volatility spillovers between two return series. See(Adrangi (2015), Koutmos (1996, 1998, 1999), Cheung and Ng (1992), among others).

We estimate the following bivariate VAR-EGARCH in equations:

$$R_{it} = \alpha_{i,0} + \sum_{j=1}^{2} \alpha_{ij} R_{i,t-1} + \varepsilon_{i,t}, \qquad \text{i,j=1,2,} \tag{12}$$

$$Ln(\sigma_{i,t}^2) = \beta_{i,0} + \sum_{j=1}^{2} \beta_{ij} \varphi_j(z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-1}^2), \ \text{i,j=1,2,} \tag{13}$$

$$\varphi_j(z_{j,t-1}) = (\left| z_{j,t-1} \right| - E(\left| z_{j,t-1} \right|) + \delta_j z_{j,t-1}), \qquad \text{i,j=1,2,} \tag{14}$$

re

$$z_{j,t} = (\left| u_{j,t} / \sigma_{j,t} \right| - \sqrt{2/\pi}) + \delta_j u_{jt} / \sigma_{j,t}$$

$$\sigma_{i,j,t} = \rho_{i,j}\sigma_{i,t}\sigma_{j,t}, \qquad \text{i,j=1,2,} \tag{15}$$

ε_{it} is the percentage daily returns in market i and time t, $\sigma^2_{i,t}$, and $\sigma_{i,j,t}$ are the conditional variance and covariances in market i, and between markets i and j, at time t, respectively, ρ_{ij}, the conditional correlation coefficient between markets i and j, $z_{i,t}= \varepsilon_{it}/ \sigma^2_{i,t}$, is the standardized innovations of market i at time t.

Equation (13) is the natural log of the conditional variance for each market, where γ_i measures the volatility persistence and its magnitude. Unconditional volatility is finite when $\gamma_i <1$, while $\gamma_i = 1$ implies non-stationary, explosive unconditional volatility (e.g., Nelson (1991) and Hsieh (1989)). Equation (14) captures the asymmetric effects of shocks on the conditional volatility, where z_{jt} is a function of innovations of the VAR equation. The derivative of ϕ (z) with respect to z j,t-1 measures the asymmetric effect of the positive and negative standardized own- and cross shocks on conditional volatility. To estimate the size and sign effects of the standardized innovations, we examine the ϕ (z). Depending on the standardized shocks and cross market shocks, $|Z_{j,t-1}|- E(Z_{j,t-1})$ may be positive or negative. The sign effect of shocks depends on $\delta_j Z_{j,t-1}$. For example, if $\delta_j>0$ and $\beta_{ij} <0$, the positive shocks in market j would contribute to volatility in market i more than the negative shocks. The asymmetric size effect is computed as $|-1+\delta_j|/(1+ \delta_j)$.

The log likelihood function to be maximized is given by

$$L(\Omega) = -.05*(n*T)\ \text{Ln}\ (2\pi)-0.5 \sum_{t=1}^{T}(Ln\left|\Lambda_t\right| + \varepsilon_t^{'}\Lambda_t^{-1}\varepsilon_t),$$

Where Ω is a vector of 16x1 model parameters, n is the number of equations in the system, i.e., two in this paper, T is the number of observations in the sample, $\varepsilon'_t =[\varepsilon_{1,t}, \varepsilon_{2,t}]$ is the vector of innovations at time t, Λ_t is the 2x2 time-varying variance and covariance matrix, with its diagonal elements given by equation (13) and the off-diagonal covariances given by equation (15). We utilize a combination of the simplex method and Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm to maximize $L(\Omega)$. The BFGS method converges if the function has a quadratic Taylor expansion near an optimum.

Data and Summary Statistics

We study the daily asset and crude oil prices for the period of December 2010 through October 2014, roughly nine hundred seventy daily observations. West Texas Cushing crude oil prices, the dollar/euro rate (the dollar), and gold prices are spot values. Generic yellow corn and soybean contract prices are the nearby futures contract prices settled at the Chicago Board of Trade. Nearby commodity contract prices reflect spot prices closely. All data are taken from the Bloomberg

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database. Percentage changes in price levels are obtained by taking the ratio of natural logs of the prices, $R_t = (\ln(P_t/P_{t-1}))\cdot 100$, where P_t represents the daily closing values.

A casual examination of crude oil and other asset prices suggests that prices are mean and covariance nonstationarity. On the other hand, the percentage change in futures prices of crude oil appear mean-stationary, but may be covariance non-stationary. Figures 1 through 5 show the graphs of daily percentage changes of these prices. The graphic evidence calls for formal statistical testing of the data.

Table 1 presents the summary statistics for the asset prices and the diagnostics for the return series. The returns series appear stationary employing the Augmented Dickey-Fuller (ADF), Phillips-Perron and KPPS statistics. There is evidence of both, linear and nonlinear dependence, as indicated by the Q and Q^2 statistics, and ARCH effects are indicated by the ARCH (6) chi-square statistic. The results in Table 1 may be summarized as follows: (i) there are clear indications that nonlinear dynamics are generating the daily prices; (ii) these nonlinearities may be due to ARCH effects. To rule out chaos as being responsible for the nonlinear dynamics, we employ correlation dimension- and BDS statistics on returns and errors from a variety of frameworks that capture the likely ARCH effects.

Empirical Results

Correlation Dimension Estimates

Table 2 reports the correlation dimension (SC^M) estimates for the returns under study, along with those for a known chaotic process, the logistic series that we developed. The results are for AR transformed data as well as GARCH (1,1) standard errors. The lag length for the AR framework,

$$R_t = \sum_{i=1}^{p} \pi_i R_{t-i} + \varepsilon_t$$

Based on the Akaike (1974) criterion. The residual term (ε_t) represents the index movements that are purged of linear relationships. The mean equation of the GARCH model is the same as given in equation (7) while the conditional variance equation of the model is given by equation (8). The standard errors from the GARCH(1,1) model are deployed in the tests for chaotic structure.

The results in Table 2 show that SC^M estimates for the logistic map (shown here for comparative purposes) hover around one as the embedding dimension rises. These estimates are not sensitive to the AR transformation and are consistent with chaotic behavior. For the asset price series, the SC^M estimates show behavior that is inconsistent with chaotic structures. The SC^M statistic for the AR and GARCH(1,1) transformation do not vary much and do not settle with the increasing embedding dimension. These findings suggest that the series under consideration are not showing signs that are consistent with low-dimensional chaos.

BDS Test Results

Tables 3 and 4 present BDS statistics (Brock, Dechert and Scheinkman (1987)) for the AR series and the standardized residuals ($\varepsilon/\sqrt{h}$) from the GARCH (1,1) models, respectively. According to the BDS statistics in Table 3, the null of no nonlinearity in the AR errors is rejected for each of the return series. On the other hand, the BDS statistics for standardized residuals from the GARCH(1,1) models are mostly insignificant at the 1 and 5 percent significance levels. These results suggest that the nonlinear dependencies in the asset and oil prices in this study arise from GARCH-type effects. The BDS statistics presented in Table 4, suggest that variations of the GARCH model may explain the nonlinearities in the series under study.

Bivariate GARCH Model Results

The results in Tables 3 and 4 provide fairly strong support for GARCH effects in the data. Therefore, we turn to Bollerslev's (1986) GARCH (1,1) model, which has also been shown to perform well in multivariate applications (e.g., Baillie and Bollerslev (1990)). The natural extension of GARCH (1,1) model for investigating the relationship between two or more variables is a bivariate VAR-GARCH (1,1) model. This model is capable of showing volatility spillovers which may signal information flow between multiple markets (e.g., Ross (1989)).

Table 5 reports the results of the bivariate GARCH (1,1) models of equation (9–11) fitted to crude oil price and each asset price in the sample. The framework appear to capture volatility in each series quite well. Most model coefficients are statistically significant at commonly expected levels of significance. In all cases, the conditional variances of returns series are sensitive to their past volatilities, a sign of ARCH effects.

The coefficients of the lagged squared Intermarket shocks (α_3) are mostly statistically significant. The implication is that volatility spillovers from crude oil market to other assets except for of corn. The systematic spillover of volatility suggests that the information arrives in crude oil markets and subsequently flows to the other markets. The exception of the corn market is somewhat puzzling. The explanation may lie in the liquidity of this market. Corn markets constitute an important component of the international grain market and has an extremely liquid futures market. Thus, the market for corn may adjust to its supply, demand and inventory conditions.

The diagnostics of the residuals reported in Table 5 show that some linear and nonlinear relationships in innovations of all equations continue to persist. More importantly, we find consistent significant cross-equation linear correlation among innovations of the estimated models. These findings may be seen as further support for the modeling of the dynamic volatility in a joint bivariate form.

Note that the coefficient of own lagged variance is barely less than 1. The magnitudes of these coefficients may be confirming the findings of previous research that restoration of prices to their long-run trend levels suggested by mean-reversion may be slow.

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On the other hand, the conditional covariance equations do not present strong support for cross-market shock interactions. Many coefficients are statistically insignificant. However, given the significance of variance equation and sign and size bias tests, as well as Q statistics of the residuals, we conclude that the volatilities show cross market spillover between the oil price and most of the asset markets in this sample.

Bivariate EGARCH Model Results

The statistical significance of size and sign bias tests provides clues that the volatility transmission may follow an asymmetric process. For that reason, we test for robustness of our results using an EGARCH framework. Table 6 reports the estimation results of the VAR-EGARCH model of equations (12)-(15) for crude oil price and other assets under study.

For all bivariate models δ_1 and $\delta_2<0$ along with positive β_{12} and β_{21}, verifying that volatility transmission across markets is asymmetric. Statistically significant $\delta_j <0$ coefficients indicate the presence of asymmetric volatility effects in each market, wherein negative shocks in each market lead to higher volatility relative to positive shocks.

The size effects (the degree of asymmetry, i.e.,$|-1+\delta_j|/(1+ \delta_j)$, are in the range of 1.383 to 18.802, indicating that asymmetric shock effects to crude oil markets are significantly higher than other asset markets. The size effects for the other three asset markets are far less, suggesting less sensitivity to positive innovations and negative news. The unconditional volatility in all cases is finite as indicated by γ_1 and $\gamma_2<1$.

The conditional correlation coefficient between the crude oil prices and remaining assets, given by equation (15), is the lowest at 0.121 for corn and the highest for the dollar at 0.285. This coefficient is close to 0.20 for all markets except corn. In all cases, the time-varying correlation coefficients are statistically significant but also significantly lower than unconditional correlation coefficients. This finding is in line with those of other researchers, for instance, Koutmos (1996) and Adrangi et al. (2015), who show that accounting for the conditional heteroscedasticity could result in more accurate and usually lower pairwise correlation coefficients among asset returns.

The dynamic conditional correlations (DCC) are plotted in Figures 6 through 9. DCC values are influenced by the time varying heteroscedasticity in the underlying price series. In every case except for soybean prices, the correlation between crude oil price and other asset prices demonstrate wide fluctuations over time. Thus, the relationships between these asset prices are time-varying, and the standard correlation analysis, especially in portfolio diversification decisions may be quite misleading.

The model diagnostics reported in the bottom of Table 6 show that mean of all standardized residual terms is around zero; variance are hovering around one as expected. The Q(12) and Q2(12) statistics are either insignificant or have dropped dramatically compared with those of bivariate VAR-GARCH model reported in

Table 5. Overall, statistical findings reported in Table 6 confirm that an EGARCH model, which accommodates asymmetry of shock transmission is the appropriate model for our purposes.

Finally, we use the estimated δj and βij coefficients to compute the impact of negative and positive shock transmission among markets. For instance, a one unit negative shock to market j affects the conditional volatility in market i by $(-1+\delta_j)^*(\beta_{ij})$. These findings are reported in Table 7.

The main finding is that the shock transmission between crude oil market and markets of other assets is asymmetric. Positive and negative shocks of the same size in the crude oil market have an unequal impact on the volatility in the crude oil market where the shock originated, as well as on the other markets. For instance, in all cases, positive shocks to the crude oil prices of the past period, have smaller percentage impact on the conditional volatility in crude oil and equity markets, compared to a negative shock of the same size. The market for gold shows the largest reaction in conditional volatility to a positive and negative shocks to the crude oil prices, 0.077 and 0.359, respectively. The dollar shows the smallest reaction to both types of shocks to oil prices. The average percentage response of all markets to a one percent positive shock in the previous period to oil prices is 0.037.

The Volatility reaction in all markets to own past negative innovations and crude oil price negative innovations is much larger in all markets. Second, negative shocks to lagged crude oil prices result in larger percentage impact on all current asset price volatility. The average percentage impact on the conditional volatility of all markets to negative shocks in the previous crude oil prices is 0.150, or roughly five times as large as the positive shocks. Given that the negative innovations could represent negative news in the previous period, it is natural that these shocks may roil the asset markets under study. It also may measure the investor sensitivity to negative news in the crude oil market. This finding is consistent with those of Koutmos (1996) in major equity markets of Europe.

Granger Causality Tests of Spillovers Between Asset Classes

The empirical findings thus far have shown support for the dynamic correlation between oil prices and other asset markets. Granger causality test may be another approach to investigate a causal association between the percentage change in oil price and returns to other assets in the study. We do this using a nonlinear extension of the standard Granger causality (Granger (1969), Geweke (1984)) because of nonlinearities in each returns series.

The nonlinear version of Granger causality test is based on smooth transition regression (STAR). As explained by Adrangi et al. (2015), given y_t that is generated by the STAR model, the nonlinear Granger causality boils down to testing the predictive power of lagged values of another variable, x_t, where the sequence {xt} is assumed to be stationary. The non-linear effect of x on y is characterized by an additive smooth transition component. The following additive smooth transition regression model is used,

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VER: [SC_00049-Master:11 Jul 17 02:10]**[MX-SECNDARY:** 12 May 17 07:53]**[TT-:** 23 Sep 11 07:01 loc=usa unit=00520-ch0003v6601] 0

$$y_t = \pi_{10} + \pi_1^{'} w_1 + (\pi_{20} + \pi_2 w_t)F(y_{t-d}) + \delta_1^{'} v_t + (\delta_{20} + \delta_2' u_1)G(x_{t-e}) + u_t \quad (16)$$

where δj= (δj1... δjq)', j=1, 2, ν t= (xt-1....xt-q)' and G(.) is a transition function. The null hypothesis of no causality is H0: G≡0 & δji=0, i = 1.....q. In practice, equation (16) is replaced by the following approximation,

$$y_t = \bar{\pi}_{10} + \bar{\pi}_1^{'} w_1 + (\pi_{20} + \pi_2 w_t)F(y_{t-d}) + k^{'} v_t + \sum_{i=1}^{q}{}^{'} \sum_{j=1}^{q} \phi_{ij} x_{t-1} x_{t-j} + \sum_{i=1}^{q} \psi_i x^3{}_{t-1} + u_t, \quad (17)$$

where K'= (k1.....kq), and we conclude no causality if k_i=0, ϕ_{ij}=0 and ψ_i=0 i=1...q, j=1...q. The null hypothesis is tested by the statistic which has an asymptotical F distribution with (q*(q+1)/2) +2q degrees of freedom.

Table (8) summarizes the findings of the nonlinear Granger Causality tests for q =5....10. The null hypothesis is no Granger causality, i.e. k_i=0, ϕij=0 and ψi=0. Following Skalin and Svirta (1999), we estimate the model for q =5....10 lag order in equation (17). P-values for the F statistic in Table 8 are virtually equal to zero for two assets, showing that the H0 is rejected and there is evidence of causality from the crude oil prices to the exchange rate of the dollar as well as soybean. This finding offers strong support for the asymmetric volatility spillovers from crude oil into markets of these assets. That is not true of corn and gold (i.e., no causality is established). As before, the results appear to suggest that the relevant information flows to the grain and crude oil markets may not be common.

The critical ramifications of these findings are multifold. First, oil price shocks spill into some agricultural products (assuming that findings for soybeans are found elsewhere), initiating inflationary trends in food prices. One implication of this finding is that relying on the core rate of inflation as advocated by most central banks and the Fed may be appropriate. Otherwise, temporary volatilities in the crude oil market distort the CPI-based inflation rate and lead to misplaced policies calculations throughout the economy.

Second, gold prices do not seem to be directly caused by crude oil price volatility. However, based on EGARCH model estimates, gold prices are closely associated with volatilities in the crude oil market. Therefore, gold maintains its real value in the face of price uncertainties triggered by crude oil prices. Therefore, gold investments may offer a "safe haven" against market vagaries stemming from volatile crude oil markets because gold prices react to these volatilities. It may also explain some of the popularity of gold as an instrument of a hedge against uncertainties in financial and broader markets.

Finally, the finding that the exchange rate of the dollar is responsive to crude oil price shocks may represent a similar reaction by other major currencies of the world. Generalizing the findings here to other major currencies may be a subject of a future research. However, with this leap of faith, one can conclude that the real exchange rate among major currencies may remain unaffected by volatilities in the crude oil markets. Therefore, the current account effects of crude oil price volatility may be minimal.

Summary and Conclusions

This study examines the volatility spillovers between crude oil prices and four other assets. We find that the price series are nonstationary, and returns exhibit nonlinear dependencies that are inconsistent with chaotic structure. Bivariate VAR-GARCH models indicate volatility spillovers from crude oil market into three out of four assets under study. Initial results also offer support for asymmetric market responses to negative and positive shocks. Therefore, we also propose and estimate asymmetric bivariate VAR-EGARCH models. The results from these models provide evidence for asymmetric shock transmission. Thus, positive and negative shocks of the same size have an unequal effect on the volatility of the other markets. We compute these shock effect and demonstrate that volatility responses and spillovers are much more elevated following negative news in each market. For instance, in all cases, positive shocks to the crude oil prices of the past period, have smaller percentage impact on the conditional volatility in crude oil and equity markets, compared to a negative shock of the same size. The negative news in crude oil markets convey bad economic news, possibly suggesting recessionary trends.

The gold market shows the largest reaction in conditional volatility to a positive shock to the crude oil prices while the market for the dollar shows that smallest reaction. The average response of all markets to a positive shock in the previous period to oil prices is 0.037. The volatility reaction to negative innovations in crude oil prices results in larger percentage impact on the volatility of gold and soybeans than corn and the dollar. While we do not see a consistent pattern of response for any given commodity, apparently the gold markets are quick in responding to the crude oil market shocks. Therefore, gold may be considered a reliable hedge against inflation. The pronounced response of gold prices to shocks in crude oil market "bad" news may indicate that the gold market is efficient in the information transmission and, thus, far more responsive to both positive and negative lagged shocks in crude oil prices.

The dollar exhibits the least volatility in response to lagged positive and negative crude oil market shocks. The average percentage impact on the conditional volatility of all markets to negative shocks in the previous crude oil prices is 0.150, or roughly five times as large as the positive shocks. The negative innovations may be interpreted as negative news in the previous period. Bad news through market and investor psychology may affect the asset markets in a more pronounced way than positive news of equal size. Observing empirical findings that indicate dynamic market interactions and volatility spillovers at least for some of the assets under study, we test for Granger causality to complete our investigation.

Given the underlying nonlinear relationships among the variables under consideration, we employ the nonlinear version of the Granger causality test based on smooth transition regression (STAR). The empirical findings show that crude oil prices Granger cause the dollar and soybeans, but not corn and gold. The nonlinear causality test results are robust for all lag structures considered in the empirical tests.

The main findings of the study are as follows. First, the US agricultural commodity market volatility is associated with crude oil price volatility. The dollar reacts to crude oil prices, but the speed, and magnitude of this reaction are relatively small. Gold prices are not caused by crude oil price in Granger sense. However, the magnitude of the reaction of gold prices to shocks to crude oil prices suggests that crude oil price movements trigger inflationary or disinflationary concerns in the market.

The critical ramifications of these findings are multifold. First, oil price shocks spill into agricultural products (assuming that findings for soybeans may be generalized). Nonlinear Granger Causality test support this hypothesis. Therefore, relying on the core rate of inflation as advocated by most central banks and the Fed may be appropriate.

Second, gold prices do not seem to be directly caused by crude oil price volatility. However, based on EGARCH model estimates, gold prices are closely associated with volatilities in the crude oil market. Therefore, gold maintains its real value in the face of price uncertainties triggered by crude oil prices. Thus, gold investments offer a "safe haven" against market volatilities stemming from volatile crude oil markets

Finally, the finding that the exchange rate of the dollar is responsive to crude oil price shocks may represent a similar reaction by other major currencies of the world. With this generalization in mind, the real exchange rate among major currencies may remain unfazed by volatile crude oil markets. Therefore, crude oil market volatility may have insignificant repercussion on the current accounts of the US and its major trading partners.

Given the wide range of macroeconomic effects of the crude oil price volatilities in major economies of the world, the US and major world economies may be well-advised to maintain a healthy strategic reserve of crude oil to be able to cope with destabilizing effects of shocks to the crude oil market.

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Table 1
Diagnostics

Returns are given by Rt=100*ln(P_t/P_{t-1}), where Pt represents closing spot or nearby contract prices on day t. ADF represents the Augmented Dickey-Fuller tests (Dickey and Fuller (1981). The Q(36) and Q_2(36) statistics represent the Ljung-Box (Q) statistics for autocorrelation of the prices, the Rt and squared values of series, respectively. The LM-ARCH(6) statistic is the Engle (1982) test for ARCH (of order 6) in residuals of a random walk model and is $\mathscr{X}_2$ distributed with 6 degrees of freedom.

Panel A: Price Levels

Interval: 12/2010-10/2014 N=973	CP	CORN	DOLLAR	GOLD	SOYBEAN
ADF_trend	-3.063	-1.842	-2.209	-2.364	-2.182
PP_trend	-3.067	-1.606	-2.208	-2.375	-2.002
KPPs_trend	0.123	0.585	0.539	0.629	0.425
Q(36)	14995.000[a]	27004.000[a]	25382.000[a]	28825.000[a]	18587.000[a]
Q^2(36)	15117.000	27498.000[a]	25410.000[a]	28433.000[a]	18739.000[a]
LM-ARCH (6)	50.057[a]	36.090[a]	51.332[a]	64.451[a]	33.954[a]

Panel B: Percentage Changes

Interval: 12/2010-10/2014 N=973	CP	CORN	DOLLAR	GOLD	SOYBEAN
ADF_trend	-32.221	-25.892[a]	-32.226[a]	-30.608[a]	-24.645[a]
PP_trend	-32.227	-35.909[a]	-32.251[a]	-30.604[a]	-32.5.83[a]
KPPS_trend	0.042	0.046	0.069	0.058	0.051
Q(36)	20.934	44.899[b]	48.639[b]	32.592[a]	47.871[a]
Q^2(36)	158.791	119.880[a]	357.421[a]	79.426[a]	127.570[a]
LM_ARCH (6)	53.176[a]	36.935[a]	39.892[a]	47.539[a]	33.700[a]

Panel C: Summary descriptive statistics for model variables. All variables are in level.

Interval: 12/2010-10/2014 N=973	CP	CORN	DOLLAR	GOLD	SOYBEAN
Mean	96.287	525.897	1.338	1493.210	1204.752
Stand Dev	7.086	66.187	0.053	182.371	73.431
Skewness	-0.140	-1.176	0.213	0.076	-1.475
Kurtosis	2.489	3.979	2.827	1.616	6.121
J-B	13.720[a]	262.976[a]	8.545[a]	78.223[a]	746.408[a]

Notes: CP, dollar, and gold are the daily spot prices for West Texas Cushing crude oil, dollar/euro daily exchange rate, and, gold price, respectively. Corn, soybean, are nearby futures contract prices at the CBOT. All data are taken from Bloomberg database. Q(36) and Q^2(36) are the Ljung Box statistics for prices and their squared values.
[a], [b], and [c] , represent significance at .01, .05, and .10, respectively.

Table 2
Correlation Dimension Estimates

The Table reports SC^M statistics for the Logistic series (w=3.750, n=2000), daily percentage changes in spot or futures prices over four embedding dimensions: 5, 10, 15, 20. AR(1) represents autoregressive order one residuals. GAR(1,1) represents standardized residuals from an AR1 - GARCH(1,1) model.

M=	5	10	15	20
Logistic	1.02	1.00	1.03	1.06
Logistic AR	0.96	1.06	1.09	1.07
CO AR(1)	4.391	7.595	10.087	12.118
CP AR(1)	4.342	8.071	11.363	14.218
DO AR(1)	4.471	7.671	9.855	11.357
GO AR(1)	4.419	8.020	11.392	14.611
SB AR(1)	4.530	8.292	11.404	14.303
CO GAR(1,1)	4.836	9.527	14.159	18.661
CP GAR(1,1))	4.837	9.806	15.031	20.629
DO GAR(1,1))	5.068	10.211	15.405	20.426
GO GAR(1,1)	5.084	10.347	15.759	21.119
SB GAR(1,1)	5.075	10.385	15.502	20.408

Notes: CO AR(1), CP AR(1), DOAR(1), GOAR(1), SB AR(1), represent AR(1) model residuals fitted to corn, crude oil, dollar, gold, and soybean, daily returns, respectively. CO_GAR(1,1), CP_GAR(1,1), DO_GAR(1,1), GO_GAR (1,1), SB_GAR(1,1), represent standardized residuals of GARCH(1,1) model.

Table 3
BDS Statistics for AR(1) Residuals

The figures are BDS statistics for the AR(1). [a], [b], and [c] represent the significance levels of .01, .05, and .10, respectively.

	M			
ε/σ	2	3	4	5
CO AR(1)				
0.50	4.715	6.584	7.124	8.491
1.00	5.031	7.008	7.589	7.987
1.50	5.206	7.338	8.106	8.454
2.00	3.776	6.255	7.309	7.581
CP AR(1)				
0.50	5.908	7.821	8.721	10.646
1.00	5.052	6.484	6.913	7.281
1.50	4.381	5.747	6.096	6.322
2.00	3.252	4.786	5.097	5.123
DO AR(1)				
0.50	2.939	4.145	5.758	7.087
1.00	3.707	4.926	5.838	6.320
1.50	3.760	4.864	5.639	5.797
2.00	3.839	4.840	5.622	5.439
GO AR(1)				
0.50	2.450	4.153	5.308	6.107
1.00	3.345	4.903	5.725	6.530
1.50	3.560	5.102	5.668	6.399
2.00	4.164	5.859	6.276	6.912
SB AR(1)				
0.50	3.585	4.807	5.435	5.695
1.00	4.229	5.584	5.825	6.196
1.50	3.895	5.519	5.775	6.139
2.00	3.185	5.076	5.339	5.659

Notes: CO AR(1), CP AR(1), DOAR(1), GO(1), SB AR(1),, represent AR(1) model residuals fitted to, crude oil, corn, dollar, gold and soybean daily returns.

Table 4
BDS Statistics for GARCH (1,1) Standardized Residuals

The figures are BDS statistics for the standardized residuals from GARCH(1,1) models. The BDS statistics are evaluated against critical values of standard normal distribution. [a], [b], and [c] represent the significance levels of .01, .05, and .10, respectively.

	M			
ε/σ	2	3	4	5
CO_ GAR 11				
0.50	1.876	2.749	2.616	2.769
1.00	1.799	2.561	2.278	2.079
1.50	1.731	2.499	2.351	2.129
2.00	0.759	1.597	1.679	1.596
CP_ GAR 11				
0.50	2.274	2.353	1.551	1.206
1.00	2.490	2.865	2.293	1.812
1.50	1.447	2.289	1.888	1.527
2.00	0.353	1.141	0.922	0.638
DO_ GAR 11				
0.50	-0.093	-0.226	-0.126	-0.490
1.00	-0.037	0.119	-0.096	-0.588
1.50	0.281	0.406	0.441	-0.300
2.00	0.188	0.263	0.408	-0.567
GO_ GAR 11				
0.50	-1.455	-0.788	-0.573	-0.656
1.00	-1.488	-0.921	-0.680	-0.519
1.50	-0.927	-0.665	-0.789	-0.645
2.00	-0.495	-0.345	-0.047	-0.054
SB_ GAR 11				
0.50	0.062	0.289	0.010	-0.226
1.00	1.154	0.439	-0.121	-0.450
1.50	0.571	1.182	0.768	0.413
2.00	0.648	1.859	1.734	1.449

Notes: CO_GAR 11, CP_ GAR 11 DO_ GAR 11, GO_GAR 11, SB_ GAR,1, represent standardized residuals of GARCH(1,1) model residuals fitted to, crude oil, corn, dollar, gold and soybean daily returns.

Table 5

Mean Equation	Crude	Corn	Crude	dollar	Crude	Gold	Crude	Soybean
Intercept	-0.016	-0.084	-0.019	-0.012	0.020	-0.002	-0.045	-0.026
	(0.044)	(0.038)	(0.051)	(0.017)	(0.064)	(0.042)	(0.059)	(0.031)
Own Lagged	0.012[a]	7.382[a]	-0.011	16.659[a]	-0.005	18.869[a]	-0.046[b]	9.043[a]
	(0.029)	(0.021)	(0.032)	(1.332)	(0.003)	(0.023)	(0.027)	(3.017)
Corss Lagged	-0.151[a]	-7.382[a]	-0.154	-6.659[a]	-0.074[a]	-1.879[a]	0.002	-90.330[a]
	(0.034)	(0.010)	(0.097)	(0.013)	(0.025)	(0.015)	(0.052)	(31.702)
Variance Equation	**Crude**	**Corn**	**Crude**	**dollar**	**Crude**	**Gold**	**Crude**	**Soybean**
Intercept	0.026[a]	0.110[a]	1.449[a]	0.601	0.055[a]	0.003	-0.048[a]	0.701[a]
	(0.010)	(0.028)	(0.295)	(0.561)	(0.013)	(0.068)	(0.014)	(0.093)
Lagged Conditional Variance	0.953[a]	0.871[a]	0.296[b]	-0.954[a]	0.926[a]	0.963[a]	0.951[a]	0.144[a]
	(0.008)	(0.032)	(0.135)	(0.171)	(0.011)	(0.004)	(0.009)	(0.098)
Lagged Own Shocks	0.019[a]	0.044[a]	0.042[a]	-0.016	0.053[a]	0.019[a]	0.013[a]	0.103[a]
	(0.005)	(0.012)	(0.019)	(0.003)	(0.010)	(0.001)	(0.003)	(0.034)
Intermarket Lagged Shock	0.020[a]	0.006	0.605[a]	-0.008[a]	-0.004	-0.002[b]	0.026[a]	-0.008[a]
	(0.005)	(0.005)	(0.201)	(0.002)	(0.007)	(0.001)	(0.007)	(0.003)
Ho: Intermarket lagged shocks are equal	χ^2 =1029.405 [a]		χ^2 =4.834b		χ^2 =6758.754a		χ^2 =9615.437a	
Conditional Covariance Equation								
Intercept	0.001		0.198[a]		0.002		0.213	
	(0.002)		(0.092)		(0.002)		(0.137)	
Lagged Conditional Covariance	0.975[a]		0.355		0.985[a]		0.069	
	(0.152)		(0.298)		(0.008)		(0.518)	
Product of Lagged Residuals	0.006		-0.018		0.008[a]		0.023	
	(0.007)		(0.019)		(0.003)		(0.019)	
Diagnostics on Standardized residuals								
Q(12), ε_t/σ	4.295	30.572[a]	2.077	24.045[a]	4.050	38.182[a]	4.039	28.450[a]
Q(24), ε_t/σ	10.149	39.984[a]	10.614	47.189[a]	9.811	48.756[a]	11.080	41.250[a]
$Q^2(12)$, ε_t^2/σ	14.594	15.024[c]	31.544[a]	97.508[a]	11.581	50.055[a]	26.664[a]	35.307[a]
$Q^2(12)$, ε_t^2/σ	23.409	37.011[a]	59.411[a]	254.376[a]	16.819	51.806[a]	40.159[a]	84.122[a]
Q(24), $\varepsilon_{it}\,\varepsilon_{it}/\sigma_i\,\sigma_j$	40.754[a]		76.894[a]		27.169		47.064[a]	
System Log Likelihood	-1589.449		-779.1180		-1418.228		-1331.906	

Bias t-Statistic	Equation 1	Equation 2						
ias	10.269[a]	10.911[a]	1.974[a]	-1.059	1.968[a]	1.734[c]	2.268[a]	1.299
negative shock size bias	11.75[a]	-1.768[c]	-2.370[a]	-2.673[a]	-2.219[a]	-6.369[a]	0.122	-0.823
positive shock size bias	12.759[a]	13.375[a]	-0.066	0.324	-0.829	-0.872	-0.220	-0.855
Joint sign and size bias (χ^2)	4.699	5.821	8.114[b]	18.768[a]	5.763	42.948[a]	9.907[a]	1.692

Notes: Returns and conditional variance equations are estimated in a system assuming variance correlations are constant. Q and Q^2 are the Ljung-Box statistics of the autocorrelation in the standardized residuals ($\varepsilon_{it} / \sqrt{\sigma_{it}}$) and their squared values. The sign and size bias tests show whether asymmetric model may be appropriate. (see Engle and Ng (1993)).
[a], [b], and [c], represent significance at .01, .05, and .10, respectively.

Table 6

Bivariate Asymmetric VAR- EGARCH Model With Volatility Spillovers
Panel A: Crude Oil Price and Asset Classes

Mean Equations

Mean Equation	Crude	Corn	Crude	Dollar	Crude	Gold	Crude	Soybean
Intercept α_{10}, α_{20}	-0.026	-0.082[a]	-0.043	-0.009	-0.031	-0.014	-0.040[a]	-0.036
	(0.034)	(0.033)	(0.042)	(0.014)	(0.030)	(0.030)	(0.008)	(0.025)
Own Lagged Return α_{11} α_{21}	-0.019[a]	-0.005	-0.161[a]	-0.008	-0.028	-0.008	-0.026[a]	0.026
	(0.029)	(0.023)	(0.032)	(0.011)	(0.025)	(0.017)	(0.001)	(0.016)
Cross Lagged α_{12}, α_{22}	-0.004	-0.059[a]	-0.063	-0.023	0.019	0.019	-0.001	-0.018
	(0.034)	(0.029)	(0.073)	(0.031)	(0.046)	(0.031)	(0.008)	(0.028)
Variance Equation	Crude	corn	Crude	dollar	Crude	Gold	Crude	Soybean
Intercept β_{10}, β_{20}	0.005[a]	0.014	0.038	0.002[a]	0.028	0.025[a]	0.022	-0.007
	(0.001)	(0.003)	(0.021)	(0.0009)	(0.013)	(0.009)	(0.015)	(0.028)
Asymmetric Effect β_{11}, β_{21}	0.004	0.001	0.152[a]	-0.046	0.120[a]	0.021	0.075[a]	0.002
	(0.008)	(0.002)	(0.009)	(0.039)	(0.034)	(0.029)	(0.010)	(0.020)
Asymmetric Effect β_{12}, β_{22}	0.073[a]	0.138[a]	0.009	0.017	0.011	0.218[a]	0.071[a]	0.194[a]
	(0.011)	(0.024)	(0.003)	(0.010)	(0.022)	(0.037)	(0.009)	(0.035)
Lagged Conditional Variance γ_1 γ_2	0.999[a]	0.984[a]	0.964[a]	0.987[a]	0.974[a]	0.912[a]	0.981[a]	0.947[a]
	(0.008)	(0.005)	(0.017)	(0.004)	(0.032)	(0.034)	(0.008)	(0.026)
Lagged stand. Shock δ_1 δ_2	-0.161[a]	-0.166[a]	-0.447[a]	-0.199[a]	-0.646[a]	-0.269[a]	-0.899[a]	-0.220[a]
	(0.028)	(0.011)	(0.055)	(0.096)	(0.188)	(0.113)	(0.356)	(0.029)
Leverage Effect $\lvert -1+\delta_j \rvert/(1+\delta_j)$	1.383	1.399	2.616	1.497	3.62	1.736	18.802	1.564
Correlation		0.121[a]		0.285[a]		0.263[a]		0.220[a]
		(0.028)		(0.027)		(0.027)		(0.024)
Diagnostics on Standardized residuals								
Q (12), ε_t/σ	5.727	15.873	3.235	10.588	3.479	4.505	4.159	16.220
Q^2 (12), ε_t/σ	16.268	7.903	8.722	10.630	10.183	7.699	11.738	9.954
$E(\varepsilon_t/\sigma)$	0.006	0.023	0.016	0.009	0.007	0.004	0.127	0.011
$E(\varepsilon_t/\sigma)^2$	1.038	0.991	0.995	1.010	0.995	0.997	0.998	1.000
System Log Likelihood	-3294.592		-3159.8907		-3158.306		-3046.348	

Notes: Returns and conditional variance equations are estimated in a system assuming variance correlations are constant. Q And Q^2 are the Ljung-Box statistics of the autocorrelation in the standardized residuals ($\varepsilon_{it} / \sqrt{\sigma_{it}}$) and their squared values. The sign bias test shows whether positive and negative innovations affect future volatility differently from the model prediction (see Engle and Ng (1993)).
[a], [b], and [c], represent significance at .01, .05, and .10, respectively.

Table 7

Impact of Cross Market Shocks on the Percentage Change in Volatility

Shock Origin (t-1)	Crude oil	Corn	Dollar	Gold	Soybean
Crude oil (+)	0.034	0.062	0.005	0.077	0.007
Crude oil (-)	0.141	0.086	0.013	0.359	0.135
Corn (+)	0.0008	0.115			
Corn (-)	0.001	0.161			
Dollar (+)	0.037		0.014		
Dollar (-)	0.055		0.020		
Gold (+)	0.015			0.159	
Gold (-)	0.027			0.277	
Soybean (+)	0.001				0.151
Soybean (-)	0.002				0.237

Notes: The responses of crude oil prices to crude market shocks are average for all asset markets. All cross market shocks are in absolute values.

Table 8

Nonlinear Granger Causality Test: P-Values for the F test of Ho of no Nonlinear Granger Causality

Nonlinear Granger Causality Test: P-Values for the F test of Ho of no Nonlinear Granger Causality

	Causing Variable	Caused Variables			
Lags	Crude Oil Price	Corn	Dollar	Gold	Soybean
5		0.6408	0.0132	0.4676	0.0682
6		0.7657	0.0483	0.5571	0.1083
7		0.5262	0.0413	0.7506	0.0594
8		0.1772	0.0177	0.6794	0.0466
9		0.1224	0.0038	0.3146	0.0365
10		0.0126	0.0025	0.1163	0.0138

Notes: All F statistics for the dollar and soybeans are significant at less than 1 percent significance level, with P-values virtually equal to 0. Degrees of freedom are 25, 32, 42, 52, 63, and 75 for q=5 through 10 respectively.

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VER: [SC_00049-Master:11 Jul 17 02:10]**[MX-SECNDARY:** 12 May 17 07:53]**[TT-:** 23 Sep 11 07:01 loc=usa unit=00520-ch0003v6601] **0**

Daily Asset Returns

Figure 1

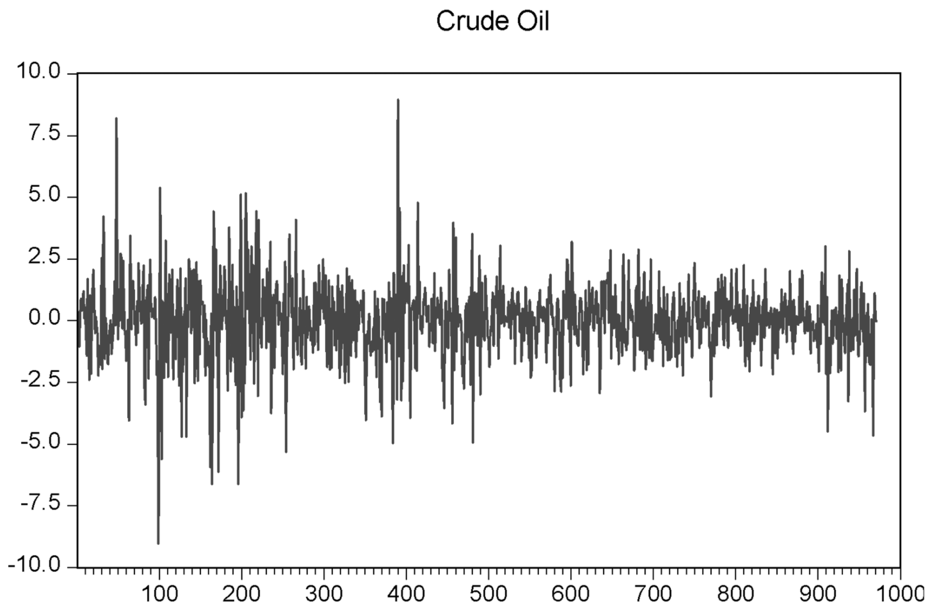

Figure 2

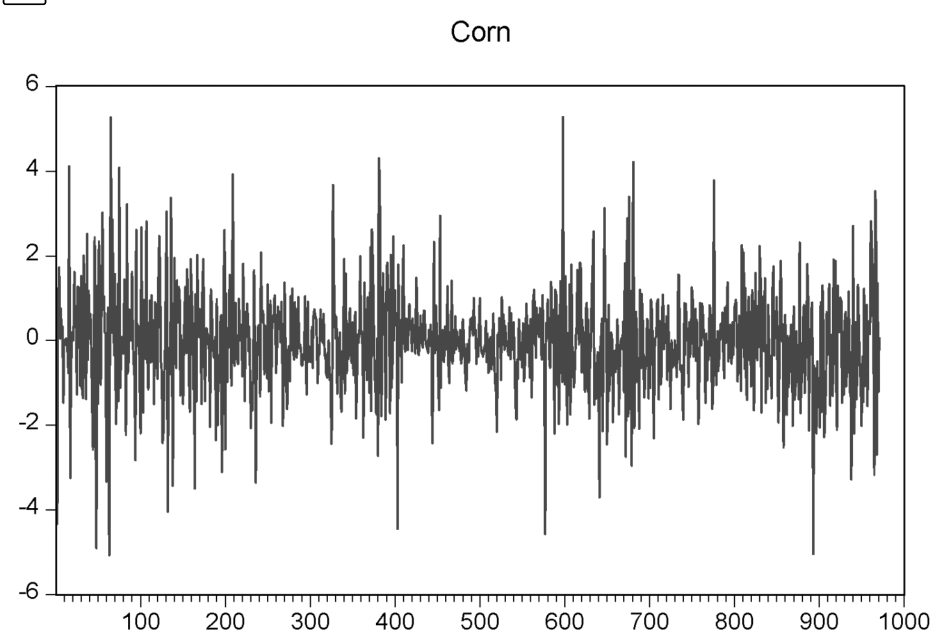

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Figure 3

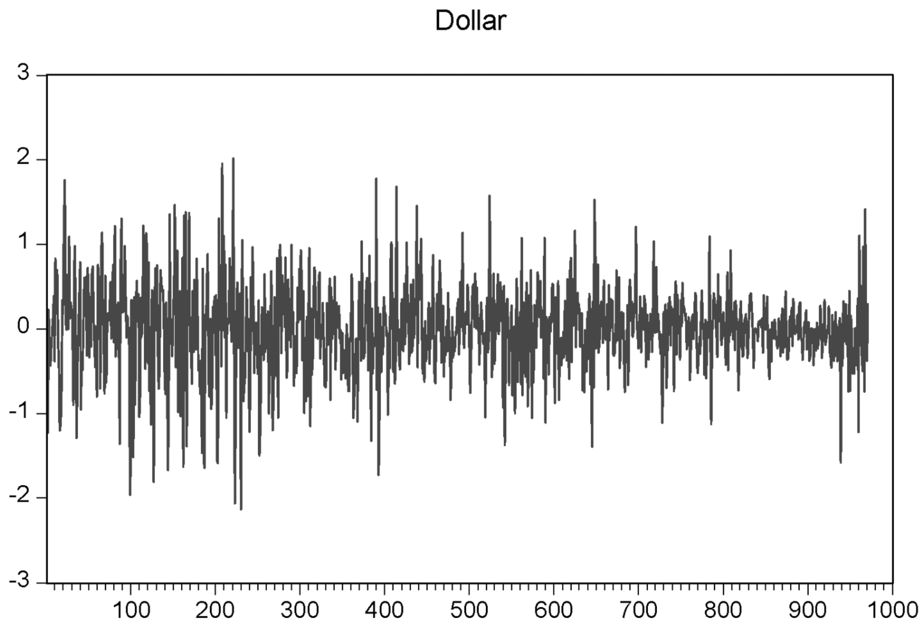

Figure 4

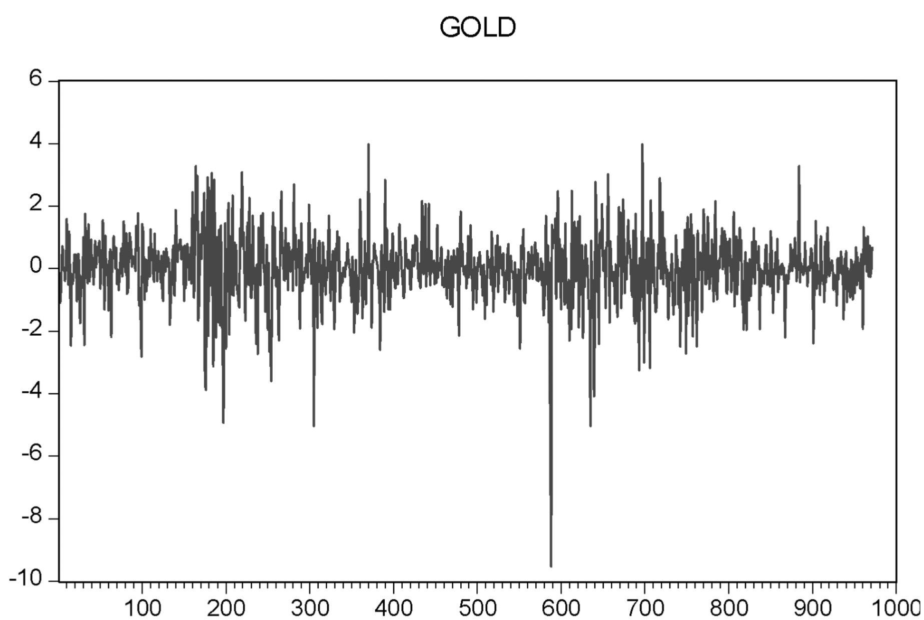

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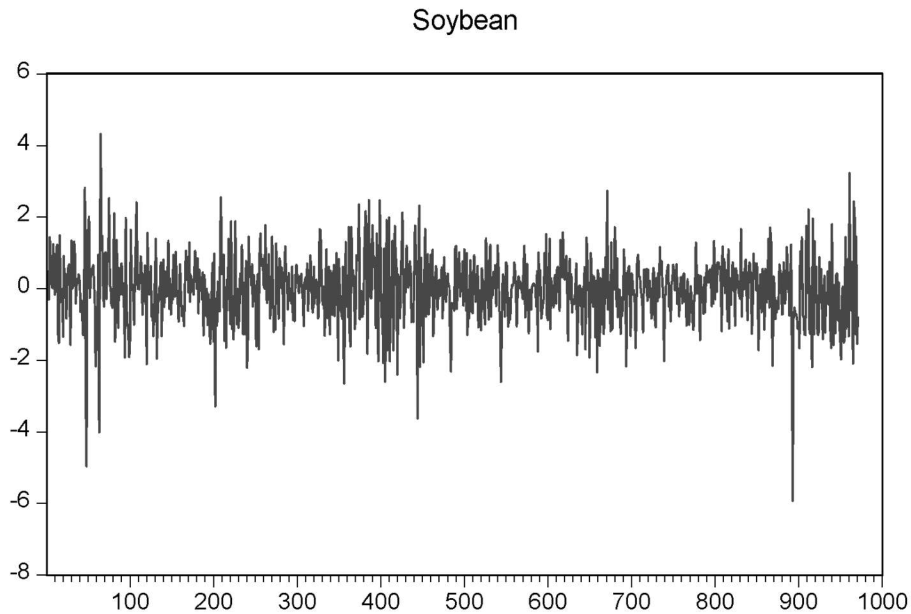
Figure 5



Dynamic Conditional Correlations

Figure 6

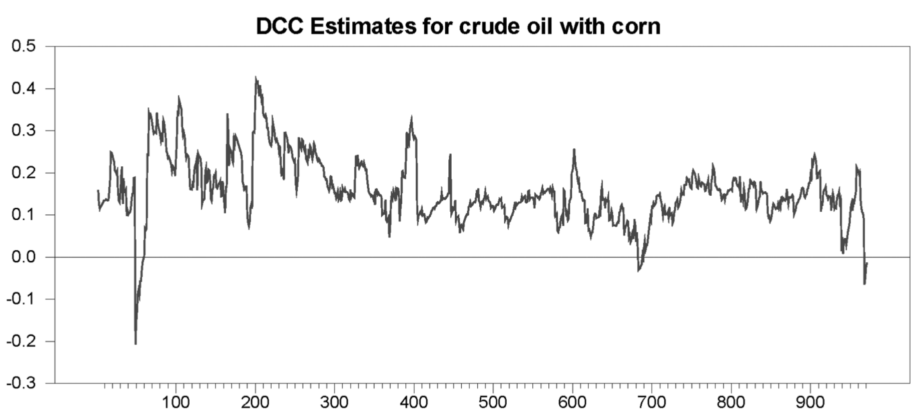


Figure 7

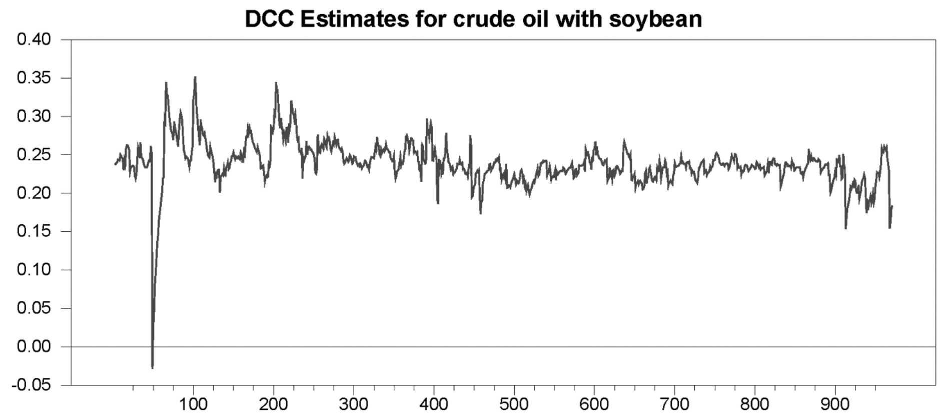


Figure 8

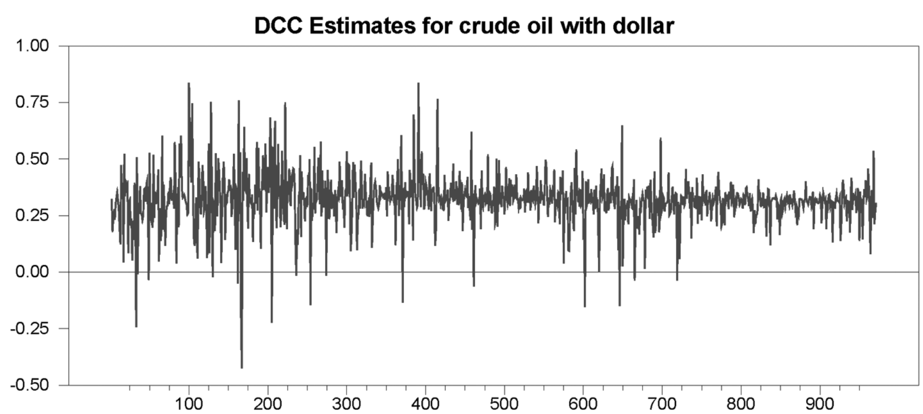
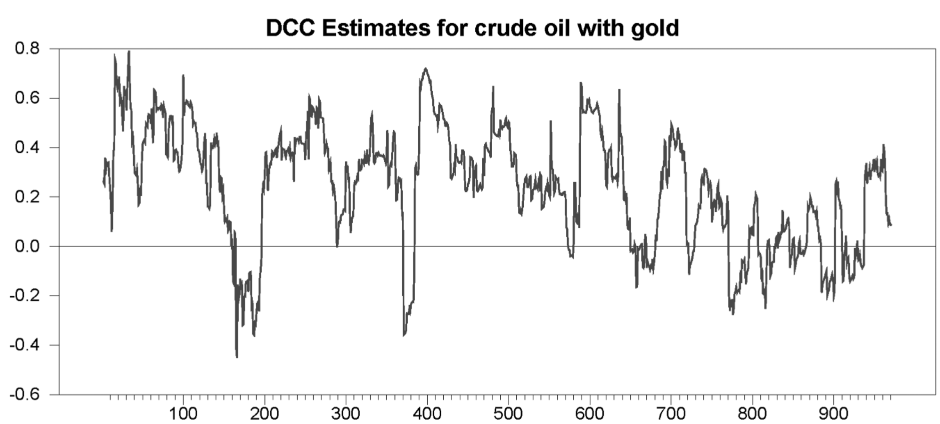


Figure 9



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